An appraisal for features selection of offline handwritten signature verification techniques

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ABSTRACT

This research provides a summary of widely used Handwritten Signature Verification based feature selection techniques. Moreover, the focus is on selected best features of signature verification, characterized by the number of features represented for each signature and the aim is to discriminate if a given signature is genuine or a forgery. We presented how the discussion, on the advantages and drawbacks of feature selection techniques, has been handled by several researchers in the past few decades and the recent advancements in the field.

Keywords: signature verification; feature extraction; dimension reduction; feature selection; handwritten signature;

1. INTRODUCTION

Handwritten signature is widely utilized and recognized technique throughout the world, the thorough testing of the signature image is important before going to the deduction about the writer. The difference in original signature makes it difficult to distinguish between the original and forgery signature. The signature identification and verification methods may develop the authentication procedures and can distinguish between the genuine and forged signatures [1]. The handwritten signature has also an adequate importance in online banking implementations and cheque processing mechanism [2]. For the authentication of passports, biometrics methods can be utilized; exactly, for the signature verification [3].

Features extraction can be defined as the characteristics of signature that are derived from that signature itself. These extracted features represented an important role in developing the robust system as all other phases are based on these features. A large number of features may decrease the value of FRR (overall number of genuine signatures discarded by the system) but at the same time it will increase the value of FAR (number of forged signatures accepted by the system). However, little effort has been done in measuring the consistency of these attributes. This consistency measurement is important to determine the effectiveness of the method. In order to measure the consistencies of these features, there is a need to choose the best attributes set among them [4]. There are two major procedures of signature identification and authentication one of them is the real identification of the signer of signature, and the other is real classification of sample whether it is an original or a forged [5].

The focus of this research will be on off-line signature authentication methods. Further parts of this study will be, in Section 2 include the literature review of the already published existing methods of off-line signature verification, Section 3 includes the critical analysis of existing research studies, and lastly in Section 4 the conclusion of the research is given.

2. PROBLEM STATEMENT

In the literature of offline handwritten signature verification, we can find multiple ways of defining the problem. In particular, one matter is critical to be able to compare related work: whether or not skilled forgeries are used for training. Some authors do not use skilled forgeries at all for training [7, 8], other researchers use skilled forgeries for training writer-independent classifiers, testing these classifiers in a separate set of users [9] lastly, some papers used skilled forgeries for training writer-dependent classifiers, and test these classifiers in a separate set of original signatures and forgeries from the same set of users.

Boosting feature selection is achieved by attributes selection methods that chooses the single most discriminant attribute of a set of the attributes and finds a threshold to detach the two categories to train, effectively a decision stump. Then, attributes are chosen in a greedy fashion according to the weighting while training is conducted by the features selection techniques. The presence of a very large number of features resulted in a committee built on the best attributes selection signifying the training samples [10]. The concept of feature selection proposes a system for signatory recognition which is based on reduced number of features from the signature [11]. Proposed a good approach of feature selection, which when applied for signature provides a good way of compressing the signature while maintaining acceptable identification rates.

3. SIGNATURE VERIFICATION

Handwritten signatures have applied as bio-metric features that distinguish persons. It has confirmed that signature samples are very faultless bio-metric feature with a low conflict proportion. Some signature samples might be comparable but there are different technical methods to distinguish between them and for disclosure of forgery signatures. There are two classes of handwritten signature verification systems:

3.1 Verification system of offline (static) signature

Signature is written offline like a signature written on bank cheques and the technique read the scan sample of the signature then obtains it with the signature samples stored in the database. Off-line signatures are shown in Figure 1.

Figure. 1 Offline signatures [12]

3.2 Verification system of online (dynamic)

Signature signing onto a reactive electronic system for example in is read on-line, and comparison of signature samples on folder of the individual to test for validity. Several selected best features are used with on-line signature samples that are not accessible for the off-line ones. Online handwritten signature is displayed in Figure 2.

Figure. 2 Online signatures [12]

4. DATASETS

The availability of datasets is one of the most important requirements in any research area. Thus, the same is the case with signature analysis and recognition. A number of datasets comprising signature samples have been developed over the years mainly to support signature verification, signature segmentation and signer recognition tasks. Especially, during the last few years, a number of standard datasets in different scripts and languages have been developed allowing researchers to evaluate their systems on the same databases for meaningful comparisons. Some notable datasets of signature samples along with their exciting measurements are presented in Table 1.

Table. 1 Summary of notable signature dataset

Dataset Name	Language	Signatures
GPDS [13]	English	8640
CEDAR [14]	English	2640
Arabic dataset [15]	Arabic	330
Japanese dataset [16]	Japanese	2000
Persian Dataset [17]	Persian	2000
Chinese NZMI dataset [18]	Chinese	1200

5. PRE-PROCESSING

For effective recognition of a signatory from offline signature samples, the signature must be distinguishable from the background allowing proper segmentation of the two. Most of the signatory identification techniques developed to date depend on selected features which are extracted from binary signatures with white background and black ink trace. An exclusion to this is the search of Wirotius [19], where the authors argue that like online signature sample, grayscale images also contain information about pen pressure, the intensity of the gray value at a particular pixel being proportional to the pen pressure.

Zuo et al. [20] also supported this idea and conducted a series of signatory identification experiments both on gray scale and binary images. The experiments on gray scale images reported slightly better results than the binary images with an overall identification rate of 98%. It should however, be noted that feature extraction from the gray ink trace is quite complex as opposed to the binary version. A large set of useful attributes can be extracted from binarized version of signature and consequently most of the contributions to signatory identification are based on binary images of signature [20]. A number of standard thresholding systems have been developed to binarize images into foreground and background [21], and these methods can also be applied to signature samples. Most of the research employs the well-known Otsu's thresholding algorithm [21], to compute a global threshold for the signature image and convert the gray scale image into binary [22].

Signature images may present variations in terms of pen thickness, scale, rotation, etc., even among authentic signatures of a person. Common pre-processing techniques are: signature extraction, noise removal, application of morphological operators, size normalization, centering and binarization [23]. The experiments on gray scale images reported slightly better results than the binary images with an overall identification rate of 98%. It should however, be noted that feature extraction from the gray ink trace is quite complex as opposed to the binary version. A large set of useful attributes can be extracted from binarized version of signature and consequently most of the contributions to signer identification are based on binary images of signature [24].

6. FEATURE EXTRACTION

6.1 Global and local feature extraction

Local and global features include data, which are efficient for signature confession. The features choosing is that various features are necessary for any style confession and classification method. Global attributes are extracted from the complete signature. The set of these local and global attributes is further applied for reporting the identity of documentation and forgery signature samples from the dataset. The global attributes that are extracted from sample are described as follows [25].

Width (Length): For a binary image, width is the dimension between 2 pixels in the horizontal projection and must include more than three points of the signature.

Height: Height is the dimension between 2 pixels in the vertical projection and must include more than three points of the signature for a binary signature.

Aspect ratio: The proportion is a global attribute that represents the ratio of the width and the height of the signature image [26].

Horizontal projection: Horizontal projection is calculated from both binary and the skeletonized signatures. The set of dark points are calculated from the horizontal projections of binary and skeletonized images.

Vertical projection: A vertical projection is presented as the set of dark points achieved from vertical projections of binary and skeletonized images.

Local attributes extracted from gray level, binary signatures. From the small areas of the whole signature, local attributes represent, height, width, aspect proportion, horizontal, and vertical projections. To get a group of global and local attributes, both of these attributes groups are collected into an attribute vector that are represented as input to the classification techniques for matching [27, 28].

6.2 Orientation

Orientation represents the direction of the image lines. This attribute is necessary and helps to know how the signatory signed down the image, which letters come first confirming towards corners and peaks. Orientation is obtained by using the proportion of angle at main axis [29].

7. DIMENSION REDUCTION

This section introduces, the reduction of the dimension, difficulties in classification for high dimensional multivariate. Figure 3 shows the main idea of this study.

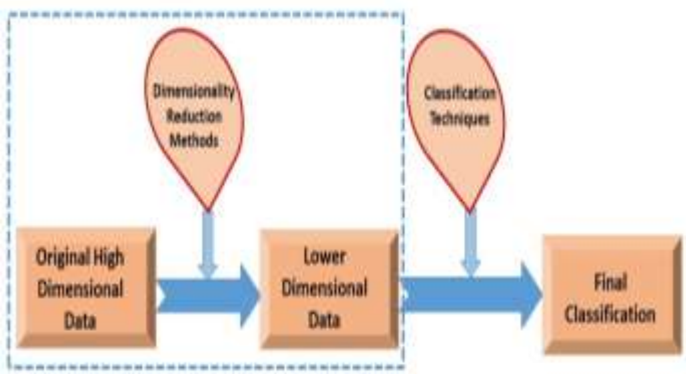


Figure. 3 Representation data of the data reduction methods

The basic concept is to decrease large amounts of information down to the significant parts. Data reduction is the procedure of decreasing the set of arbitrary inputs under consideration [32]. It can be split into attribute selection discussed in detail in next sub-sections and feature extraction. There are benefits of data reduction as it enhances the achievement of the machine training model. The first part of dimension reduction is feature selection methods, which is a try to find the original features. In some situations, information test such as classification can be done in the reduced area more exactly than in the original area such as Sparse PCA technique [33]. Linear and nonlinear reduction methods have been suggested in recent time which depend on the estimation of local data. This section shows a logical comparison of these methods. By identifying the weaknesses of current, linear and nonlinear techniques.

7.1 Linear dimension reduction

Linear methods achieve dimension reduction by combine the information into a sub area of lower dimension. There are different methods to do so, such as Linear Discriminant Analysis (LDA), and Principal Component Analysis (PCA) [33]. LDA is a popular data-analytic tool for studying the category relationship between information points and LDA is supervised. A main disadvantage of LDA is that it fails to find out the local geometrical object of the data manifold [34]. Dimension reduction is the task to reduce the amount of available data (data dimension). The data processing required in dimension reduction, of ten times linear for computational simplicity, is determined by optimizing an appropriate figure of merit, which quantifies the amount of information preserved after a certain reduction in the data dimension. The ‘workhorse’ of dimension reduction comes under the name of PCA [33]. PCA has been extremely popular in data dimension reduction since it entails linear data processing.

7.2 Non-linear techniques for dimension reduction

This section discusses two non-linear methods for dimension reduction named as Kernel PCA (KPCA) and Multi-Dimensional Scaling (MDS). These methods attempt to maintain the original data in the low dimensional performance [36]. Shown in Figure 4 KPCA calculates the kernel matrix K of the variables points xi. KPCA is Kernel based method. As shown in Figure 4 the mappings performed by Kernel principal component depends on the selection of the kernel task. A main shortcoming of KPCA is that the size of the kernel is ratio to the square of the set of cases in the database [37].

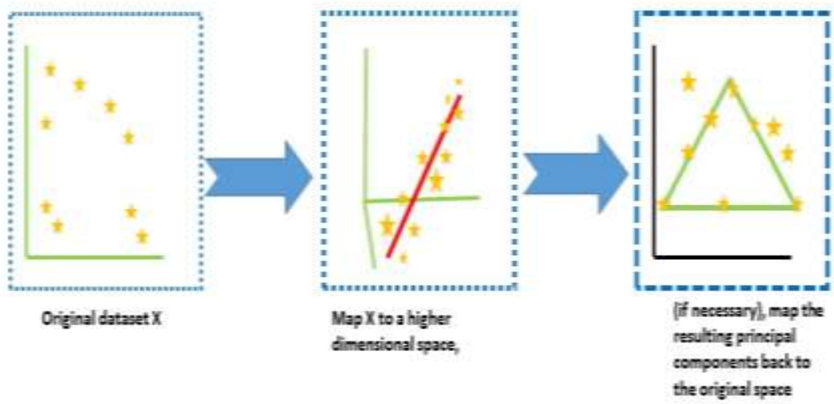


Figure. 4 Kernel principal components analysis

Honarkhah et al. [38] represented MDS but a major disadvantage of MDS provides a global measure of dis/similarity but does not provide much insight into subtleties [34]. The susceptibility to the curse of dimension and the problem in finding the small eigenvalue in an eigen problem. The PCA is susceptible to the relative scaling of the original attributes [39]. Feature extraction produces new features from the original features, while feature selection returns a subset of the original features [40]. The set of PC<= the set of original features as shown in Figure 5 (a). Orthogonal directions of greatest variance in data projections along PC1 discriminate the information mostly along any one X new X of PC as shown in Figure 5 (b).

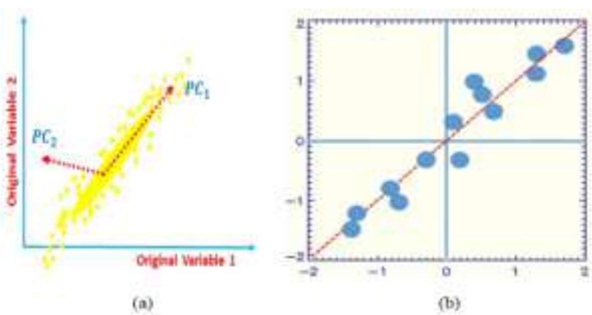
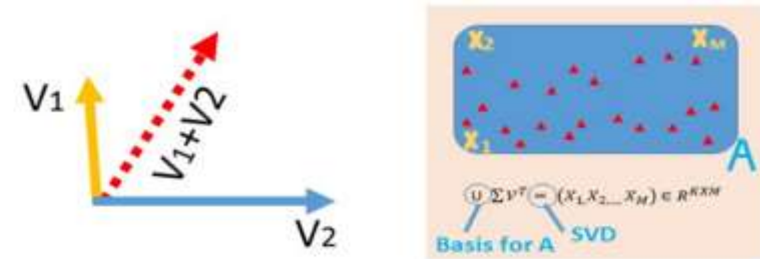


Figure. 5 (a & b) Principal components analysis

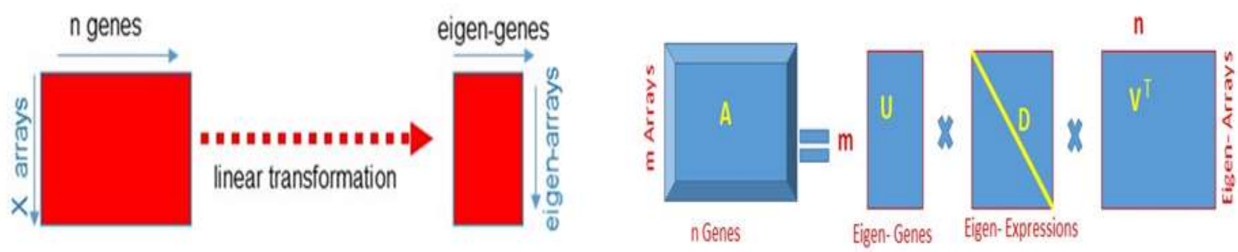
In Figure 6(a) & (b) PCA can be found via compute the Singular Value Decomposition (SVD) of matrix factorization is XTX complex matrix (empirical covariance matrix of X). V1 represents vector (yellow) is added to another vector V2 (blue), SVD is a factorization of a real.



(a) (b)

Figure. 6 (a) Vector place Figure, (b) singular value decomposition (SVD)

In Figure 7 (a) & (b). Each eigen-gene is expressed only in the corresponding eigen-array with the corresponding eigen-expression level. PCA can be found via compute the SVD of the features matrix. Compute the SVD of XB = UD, where SVD is singular value decomposition, UD are the principal components, the columns of V^T are the consistent loading of the primary components eigenvectors, V of which diagonalizes the covariance matrix XTX, U are called the Eigen values, XTX is covariance matrix and V are the Eigen-genes which represent sparse loading of features matrix, to make sure that the first principal component has the maximum variation.



(a) (b)

Figure. 7 (a & b) PCA on expression data

In Figure 8 the variance of X that is remained in X' is maximal. Dataset X is mapped to dataset X', here of the same dimension. The first dimension in X' e1= the PC1 is the direction of maximal difference. The PC2 (e2) is orthogonal to the first.

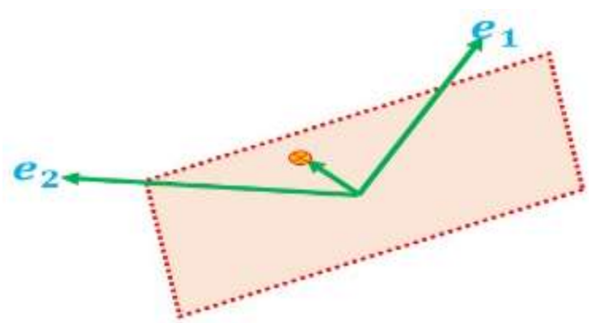


Figure. 8 Eigenvalue measures the variation in eigenvectors e

The major fragility of PCA is that the size of the covariance matrix is commensurate to the distance of the data points. As an outcome, the calculation of the eigenvectors might be infeasible for very high-distance information [35].

8. FEATURE SELECTION

Features reduction is one of the fascinating and widespread systems in offline handwritten signature verification. In some cases, current feature does not improve the capability, these features are too many (high dimensions), which reduce classification process efficiency for this we need to select best features, from features extraction as shown in Figure 9. Many researchers [41, 10] proposed features selection techniques to select features from signature image and achieved good quality results. Many papers have used a feature selection approach for signature verification. Trained a writer-independent classifier, by first extracting a large number of features from each signature (over 30 thousand features), applying feature extractors at different scales of the image. Their method consisted in training an ensemble of decision stumps (equivalent to a decision tree with only one node), where each decision stump only used one feature. With this approach, they were able to obtain a smaller feature representation (less than a thousand features) that achieved good results in the Brazilian and GPDS datasets. Eskander et al. [41] extended Rivard's [10] work to train a hybrid writer-independent-writer-dependent classifier, by first training this writer-independent classifier to perform feature selection, and then train writer dependent classifiers using only the features that were selected by the first model. This strategy presented good results when a certain number of samples per user is reached.

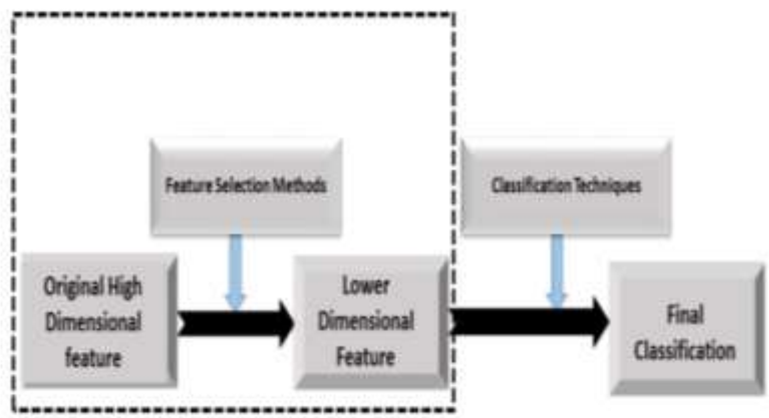


Figure. 9 Representation of best features of the features selection methods as input to classification technique

9. CRITICAL EVALUATION

The features which are selected for signature, such as Srihari et al. [30] who selected 3 types of features, Biswas et al. [42] selected 5 types of features and Pushpalatha et al. [43] selected 5 types of features. Nguyen et al. [27], Poureza et al, [28] selected 8 types of features in offline signature verification. Siddiqi and Vincent [44] selected 10 types of features in offline handwritten recognition. Each signature is represented using features selection that is the first effort of its kind in signatory recognition as shown in Table 2.

Table. 2 Number of features used in the classification, identification and verification process

Author / year	Number of Features	Types of Features
Kaler (2004) [13]	3 types of features extracted in offline Signature Verification	Eccentricity, rectangularity and orientation
Nguyen, (2007) [27], Daramola (2010) [26] and poureza (2011) [28]	8 types of features extracted in offline signature verification	Vertical projections, horizontal projections, upper profiles, lower profiles, elongation, solidity, eccentricity and rectangularity,
Biswas (2010) [42]	5 types of features extracted in signature verification	Height Width proportion of the signature, Occupancy, Dimension proportion computation at boundary, Compute the distance and Compute the set of symbols of the sample.
Pushpalatha (2014) [43]	5 types of features extracted in offline signature verification	set of Cross-points, set of edge-points, eccentricity, Mass and Centre of Mass.

Siddiqi (2010) [44]	10 types of features extracted in offline handwritten recognition	Vertical projections, horizontal projections, upper profiles, lower profiles, elongation, solidity, eccentricity, rectangularity, orientation and perimeter.

10. CONCLUSION

Several researchers have proposed different systems for verification of the signature. In spite of these advancements, the results still report somewhat large error rates for distinguishing genuine signatures and skilled forgeries, when large public datasets are used for testing, such as GPDS. This research includes a practical solution to some of the main problems encountered in the design verification of the signature, the limited set of individuals and, the large set of features from signatures, the high intra-personal variability of the signatures, and the lack of forgeries as counter examples. A new technique for feature selection is suggested for accurate design of signature verification methods. It integrates extraction and selection of the feature. Recently, feature selection methods, with classification techniques based on signer verification, have emerged as an effective way for characterizing the signer of a signature and the results of these methods are found to be better than other features for verification of the signature. As a conclusion, the method of selecting the best features among many features will help to develop the performance of verification of the signature. As this study includes the evaluation of literature in extension to this the future research suggestion is to propose new techniques that will decrease the EER.

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